Exploring the Impacts of Networks on Informational and Economic Interventions in Solar PV Adoption

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Abstract

For novel technologies such as distributed PV, effective approaches to accelerating adoption must facilitate a complex household-level decision-making process characterized by both economic and informational barriers. Using an empirically grounded and validated agent-based model (ABM) of single-family household PV adoption, the project team simulated a range of information-based strategies including recruiting interested individuals to “champion” installing solar and connecting current solar owners to potential adopters. These strategies aim to increase adoption by explicitly leveraging information exchange at the local level, which is known to be an important driver of PV adoption. Results of the information-based strategies are compared the results to a simple simulated economic-based strategy (subsidized adoption).

Three key findings emerged from the analysis. First, information-based strategies that break free of existing social networks and create new “weak ties” among previously unconnected individuals appear to be more effective than interventions that rely solely on existing personal connections to spread information. Second, when potential adopters are already densely connected and information flows freely between individuals based on pre-existing relationships, providing additional new information is necessary to increase adoption. Third, simulated information-based strategies can increase adoption with a reasonable estimated return-on-investment compared to a simulated economic-based strategy.

These findings yield two conclusions. First, information-based strategies have the potential to play an important role in PV adoption where potential adopters face informational barriers to adoption. Those interested in PV adoption may usefully continue designing, implementing, and evaluating strategies that explicitly leverage information exchange among peers. Second, information-based strategies should aim to form new ties and information exchange between individuals rather than solely leveraging pre-existing relationships. When encouraging new connections is not possible, new information—as in training—might instead be provided. Future research could explore the effectiveness of combinations of information-based and economic-based strategies when applied simultaneously.

Introduction

Relationship between Economics and solar PV adoption decision-making

Over the two past decades, there has been a global increase in efforts to support solar adoption. Global investment in solar PV is motivated by a desire to curb global warming transition to emission free energy generation. Economic incentives have been a significant driving force behind residential solar PV adoption. Federal investment tax credits (FITC), feed-in-tariffs (FIT) as well as various forms of rebates and subsidies have been introduced by governments worldwide. In Belgium, a combination of subsidies, tax credits and loans were introduced between 2002 and 2015 to increase solar PV adoption. By 2012, Belgium had a solar PV adoption rate of 8.5% (De Groote et al. 2016). In 2002, Germany introduced feed-in-tariffs to encourage the adoption of renewable energy technologies including solar PV. By 2011, the FIT policies were in their second phase of implementation, and there had been a significant increase in solar adoption in the country. By mid 2012, 5.1% of the German national electricity production was from solar PV installations (Fulton, Capalino, & Auer 2012).

The United States has also adopted policies to promote solar adoption among citizens. In 2011, the federal government disbursed $1.1 billion in form of financial assistance to increase solar adoption. This amount was a 500% increase from the amount allocated in 2007. In the same year, legislature across ten states included provisions for financial incentives to increase solar adoption (Chernyakhovskiy, Ilya, 2012). Figure 1 below presents the observed and predicted growth of installed U.S. solar PV capacity from 2010-2023 (Wood Mackenzie 2018).

In 2012, Austin's electric utility – Austin Energy - implemented the value of solar (VOS) policy. The VOS is a version of net energy metering (NEM) policies that enables these customers to receive credit for excess renewable energy generation exported to the grid. Typically, under NEM these customers are credited at the same retail rate for which the customers purchase electricity. VOS discounts the credit customers receive based on the value of the solar to the electricity grid, which Austin Energy assesses annually. In Austin, VOS replaced NEM and is only applicable in residences with solar PV systems smaller than 20kW (US DOE, 2018).

Following the implementation of NEM in Texas, state legislators began to introduce NEM legislation to their 2013 legislative session. In Q1 of 2013, there was a 53% increase in the rate of solar adoption across the US. To continue growth in PV adoption it is important for state and local governments to provide information and financial resources to sustain the increase in solar PV adoption (Noll et al. 2014).

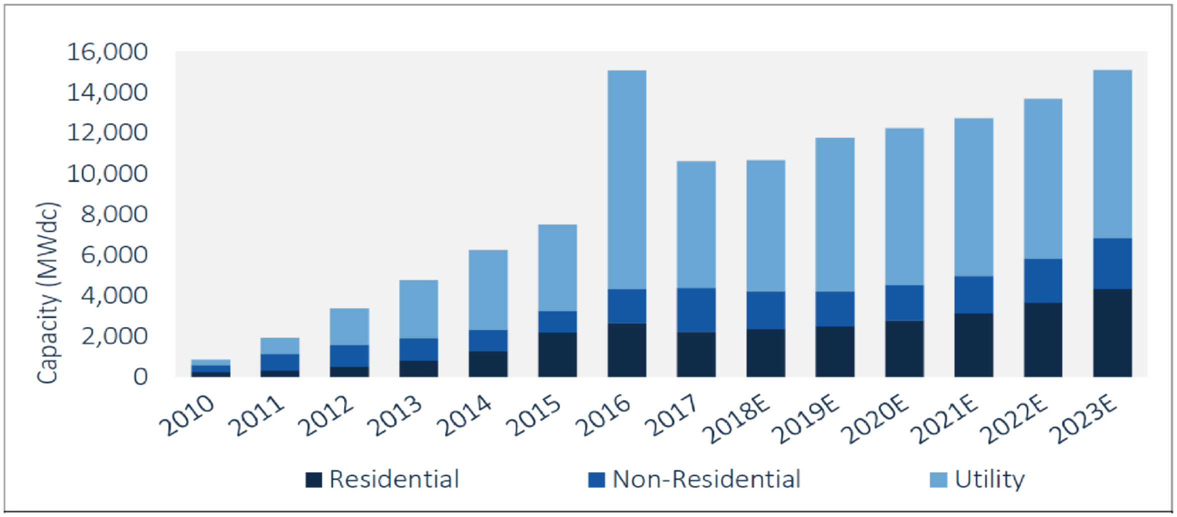

Figure 1 Empirical and predicted growth in installed capacity of Solar PV in the United States from 2010-2023 (Wood Mackenzie 2018)

Relationship between Information and solar PV adoption decision-making

Information is the adhesive that binds different choices, business structures and it is an integral part of a product's value chain (Evans & Wurster, 1997). Word of mouth (WOM) especially, is a powerful mechanism for conveying information (Jalilvand et al., 2011). Neighborhood peer-effects have been particularly effective in driving the innovation of new, risky products and have been identified as very beneficial when influential individuals in social networks are connected in ways that ease information distribution (Kumar et al., 2007). Potential solar adopters face several barriers to adoption beyond economics. Uncertainties about technology performance, adoption models (buy or lease), local policy contexts and a lack of individually relevant information complicate the decision to adopt solar PV (Rai & Robinson 2013). Information interventions – such as solar marketing and utility seminars - are a powerful resource for overcoming these uncertainties.

Peer effects are recognized to be particularly powerful in promoting the diffusion of solar PV. Bollinger and Gillingham (2012) find that each installation of solar PV in the California market increases the probability of another adoption in the same zip code by 0.78. Information interventions that are able to leverage peer effects and word of mouth have potential to reduce the uncertainty and non-monetary costs associated with PV adoption. Information interventions are able to identify the relative advantages of solar PV, demonstrate the compatibility of solar PV with a customer's belief system, reduce perceptions of technology and policy complexity and show the results of other installations (Noll et al 2014.)

This research develops an empirically justified method for modelling information and economic interventions designed to for increase solar PV adoption. We use the SECAD model – an empirically generated agent-based model of residential solar PV adoption in Austin, TX – to test and evaluate four "real-world" policy interventions designed to overcome non-monetary barriers to solar PV adoption. We assess the rate of PV diffusion by establishing baseline effectiveness metrics for various interventions in an empirically and theoretically grounded setting.

Background

Our research attempts to improve policy and bridge existing gaps between intervention targeting based on network structural characteristics and real-world solar PV interventions. We review the available literature on these topics and highlight the findings that inform our work.

Review of Solar Information Interventions

To understand the current range of information programs related to solar PV we surveyed the literature. In particular we focused on programs promoted by Solar Community Organizations (SCOs.) SCOs are formal or informal organizations that attempt to promote adoption of solar PV. SCOs provide access to credible and transparent information about the benefits of solar PV and actively campaign to promote adoption of solar PV within their operational boundaries (Noll et al 2014.)

The results of this review are summarized in Table 1. Solar information programs are diverse and vary significantly from market to market. This is likely due to the geographical variation in solar markets and solar policy across the world. As such most information campaigns are local and targeted to specific communities. Most targeted programs – such as the Solar Champions program or the Happy Hour programs - rely on individual volunteers to spread information within their communities. Other programs, including the Oregon Solar Ambassador program, create databases to connect potential solar adopters with people who have already adopted solar.

Critical to the success of solar information interventions is establishing trust between the organizations that distribute information and the recipients of information (Noll et al 2014.) Many interventions primarily focus resources on training and educating program volunteers who have established trusted relationships with their communities.

Program Type	Description
Utility Mailers / Pamphlets / Call Centers / Mass market advertising	The most extensive informational appeals to solar consumers have traditionally been through mass market mechanisms (Costanzo et al. 1986). A cursory internet search reveals that almost every solar stakeholder relies heavily on broadly distributed mass-market information such as mailers, electronic advertising and pamphlets as a primary marketing mechanism. Mass advertising, however is a highly passive form of information diffusion. Surveys show that mass media is ineffective at influencing members of the public to overcome adoption barriers to PV (Palm 2016). The high attitudinal barriers to solar adoption (Rai et al. 2016) limits the ability of passive information to leverage active peer effects to spread information.
Open House or Solar Guided Tours	Solar tours and open houses are an emerging PV advocacy mechanism. The American Solar Energy Society coordinates the National Solar Tour, where members of the public are invited to

	visit the homes of previous PV adopters. In 2012 90,000 participated in the ASES National Tour. The tour engages active peer effects by giving potential solar adopters the opportunity to interact with existing adopters. Solar tours have also been instrumental in the high rate of PV diffusion the Swedish community of Berg (Palm 2016).
Education/School Events	Solar Oregon, PGE and many other utilities install PV on Public Schools and have designed solar based curriculum training packages for teachers that fit state engineering and design and science benchmarks. Between 2004 and 2009 PGE solar curriculum was taught to over 200,000 students (Clean Energy Group 2009).
Solar Champions	Many utilities and solar advocacy organizations offer "Solar Universities." The utility recruits members of the public from neighborhoods in its service area and provides them technical education and training. These solar champions are then empowered to coordinate, train and lead solar programs in their own communities.
Porch Talks	Per members of the Mueller Megawatt project in Austin, the most effective approach to spreading solar information was what they called “porch talks.” These talks involved solar advocates who were community members sitting on their porch after dinner and asking any passerby if they knew about solar and were interested in putting PV on their roof (Noll et al. 2014)
Celebrity Endorsement	Celebrity endorsements are designed to increase customer knowledge and awareness of a product (Kowalska-Pyzalska 2017). California solar program administrators attribute part of solar take off in California to the effect of celebrity endorsement from the Governor Arnold Schwarzenegger (Clean Energy Group 2009).
Local Seminars, Happy Hours and Workshops	Attending seminars, workshops and happy hours hosted by SCOs, utilities or solar retailers is influential in the adoption process(Palm 2016). Happy hours were identified as crucial to the success of the Mueller Megawatt project (Noll et al. 2014). SCOs also coordinate workshops and seminars to educate members about the benefits of solar (Noll et al. 2014). seminars, workshops and happy hours hosted by SCOs, utilities or solar retailers is influential in the adoption process (Palm 2016). Happy hours were identified as crucial to the success of the Mueller Megawatt project (Noll et al. 2014). SCOs also coordinate workshops and seminars to educate members about the benefits of solar (Noll et al. 2014).

Group Competitions	SmartPower managed a program that organized friendly competitions between municipalities to encourage sign-ups to green power programs (Clean Energy Group 2009). Similar programs are envisioned for neighborhood solar installations. Energy Trust of Oregon approached companies that had publicly advocated for solar to run inter-company challenges to enlist employees as new solar customers (Clean Energy Group 2009)
Oregon Solar Ambassador Program	Oregon created a database where prospective solar adopters are put in contact with existing solar adopters to discuss why they chose to adopt solar. Adopters are encouraged to share key information that enabled them to overcome attitudinal barriers to solar adoption (Noll et al. 2014).

Table 1 Description of real-world solar information interventions

Review of Network Information Diffusion

The literature suggests that a small subset of influential individuals can shift the attitudes of the majority (Kovács & Barabási 2015). These influential individuals are located at central network nodes, that are most efficient at disseminating information throughout the entire network. To investigate the strength of different strategies, we incorporated network centrality in our analysis. Specifically, we explored two targeting methods for seeding information:

- Randomly seeding agents as a baseline to evaluate alternative strategies (Aral et al. 2013).
- Targeting highly connected agents (Rai & Robinson 2015; Centola & Macy 2007).

Review of SECAD ABM

Agent-based modelling enables us to study interactive aspects of an agent's life. The ability to manipulate various interactions enables us to explore the different ways through which individual decision making can manifest as observable macroscopic processes (Rai & Robinson 2015). Using ABM, we can bridge the gap between individual behavioral responses and more aggregate long-term possibilities (Hogan et al. 2004). The SECAD ABM first published by Robinson & Rai (2015) is a theoretically based model of solar adoption in Austin, Texas. The model contains ~177, 000 agents that represent each of the GIS mapped households in Austin. The model assigns economic and attitudinal attributes for each agent based on survey and property value data. The model is empirically validated and can predict adoption trends on a test data-set withheld during model fitting.

Intervention Experiments

We use the SECAD model to understand how information programs can drive adoption. In this paper, we justify how information will update attitude within the model and establish a method of determining the cost of information programs. In this research, we explore the nature of social networks and their impacts on increasing solar PV adoption.

This work will attempt to identify the characteristics of effective solar information programs. Interventions are assessed on their ability to increase adoptions while minimizing cost. The purpose of these experiments will not to be to design an optimal program that maximizes adoption for minimal cost, but to test several intervention strategies and rationalize their results. We are aiming to identify salient program features that improve adoption.

Methods

ABM Overview

We assess the impact of several practical solar information programs that currently are being implemented. Four real world information interventions – chosen from the nine presented above will be replicated within the SECAD model. Using the SECAD model we can evaluate the strength of information interventions, potential return on investment and the intervention's ability to leverage word of mouth attitude diffusion. We can also evaluate the different information strategies against one another.

The SECAD model can be used a virtual laboratory to test the efficacy of various solar interventions. The SECAD model allows testing of purely informational interventions within the model. These interventions are performed within SECAD by establishing conditions that alter the evolution of agent's socially informed attitudes within the SECAD model. Within SECAD the socially informed attitude of agents is represented by the numerical parameter *sia.* Once an agents *sia* exceeds a certain threshold ($sia_{threshold}$) they are classified as attitudinally activated. The SECAD model relies on a dual threshold model for an agent to be considered a solar adopter they must be both attitudinally and economically activated (see Figure 2). To be economically activated an agent's perceived allowable payback time is greater than their empirical payback period. These conditions may also be altered to study the outcome of economic interventions within SECAD, however economic interventions are outside the scope of this work. The desired outcome of information interventions within SECAD will be to increase individual agent's *sia* and drive solar adoption within the model.

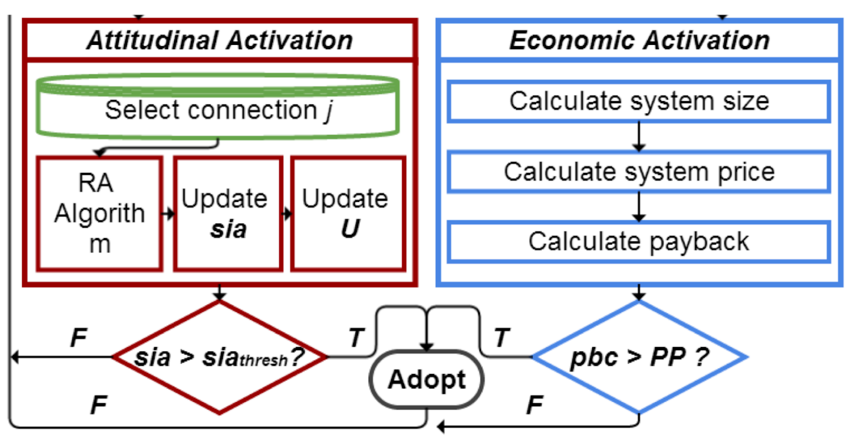

Figure 2 Flowsheet for SECAD adoption decision process (Rai & Robinson 2015)

The SECAD model allows the modeler to understand the impact of information interventions over time. At each timestep (t = 0,1,2,3,4....) agents' attitudes about solar PV (*sia*) and the uncertainties around those attitudes (U) are updated through interactions with other agents. This allows us to dynamically monitor how information interventions can manifest as attitude changes over time within the SECAD model. The layer of interactions possible in the agent-based model allows us to recreate the human reality in which various information diffusion process are interconnected.

Interaction between agents is modeled using a relative agreement (RA) algorithm (Deffuant et al., 2002, 2000; Hegselmann and Krause, 2002; Meadows and Cliff, 2012). At each time step pairs of agent's exchange attitudes with agents within their social network that share similar attitudes toward solar (*sia*) and uncertainty around those attitudes (U). A detailed formulation of the RA algorithm is presented in Rai & Robinson 2015 and Robinson & Rai 2015. For the information interventions modelled in this paper, the SECAD model ran for 24 quarters (2008-2014), with four time steps for agent updates per quarter.

Two primary types of networks – geographical and social- are defined within the SECAD model. Geographic neighborhoods around an agent *i* are defined within the model as the collection of agents that are within a certain radius (2000 ft) of agent *i*. Within SECAD the mean number of agents within each geographical neighborhood is 498.

Social networks are derived from geographical neighborhoods; however, they are further constrained by the economic similarity (calculated using home value as a proxy for wealth) of agents. Therefore, only economically similar agents were allowed in each social network. Finally, 10% of each social network's connection were randomly rewired with agents anywhere within the SECAD model, to add a degree of randomization to the social networks. It is the social networks for each agent within SECAD that dictate who each agent updates with during relative agreement. Agents will only update *sia* with other agents within their social network.

Within this paper we explore only the manipulations we make to SECAD to perform our intervention experiments. For a comprehensive explanation of the fully validated SECAD model refer to Rai & Robinson 2015 and Robinson & Rai 2015.

Selection of Real World Solar Information Programs

From the nine solar information interventions we reviewed we select four to replicate within the SECAD model. The four chosen interventions are:

- Solar Champions
- Porch Talks
- Phone Ambassadors
- Celebrity Interventions

Two primary factors dictated the choice of these programs, their similarity with other programs reviewed and their ability to leverage the social network/word of mouth interactions that govern the SECAD model. For example, pamphlets and mailers were ignored from modeling since it is unlikely that they would generate significant follow on word of mouth interactions

Solar Champions was chosen since it a program that leverages the social networks of the people who participate in the program to spread information. In this sense, it is like the Happy Hour and Workshops programs. In our modeling, we use the Solar Champion program as an umbrella for similar programs that rely on participant's social networks to spread information.

Porch talks was chosen for experimentation in SECAD since it a program that utilizes the geographic networks of participants in the program to spread information. In this sense, it is like solar open houses and guided tours, in that the intervention is confined within a local neighborhood. In our modeling, we use the porch talk program as an umbrella for similar programs that rely on participant's geographical neighborhoods to spread information.

Phone ambassadors and celebrity interventions were chosen because of their ability to spread information beyond the existing network of individuals. These programs can spread information between people who have no pre-existing connection to one another.

Informational Seeding Experiments

Seeds and Follow-Ons

Seeds are the agents who we give information too within the experimental interventions. These are the influencer agents who are able to pass on information within the model that updates other agent's attitudes. For example, in the case of the solar champions program, the seed is the agent who becomes a champion by receiving on solar training from his utility. Existing agents are chosen as seeds within the model (except for the celebrity intervention) based on either their attitude ($sia_i > sia_{thresh}$) or if they are an adopter, in which case they will still have attitude greater than the adoption threshold. Seeds by definition have high *sia*. Within each of the intervention experiments we assign between 1 and 500 agents as seeds.

Follow-ons are the agents that the initial seed agents are able to influence with the information from the intervention. Follow-ons are the agents who are influenced and update their attitudes on solar. Depending on the intervention being modeled potential follow-ons are identified as agents within a seeds social network, agents within a seeds geographical network, agents that are interested in solar (approaching attitudinal activation) or can have no pre-existing connection to the seed agent.

The final group of follow-ons is determined by randomly selecting a percentage of agents from the pool of potential follow-on agents identified in each intervention. The percentage of agents selected as follows-ons is expressed as a rate from 0-1. This is known as the follow-on rate. This rate represents how effective a seed agent is in influencing their followers.

The impact of information within SECAD

The SECAD model uses a dual threshold concept to determine whether an agent will adopt solar PV. An agent must be both attitudinally and economically activated if it is to adopt. Informational and educational solar incentive programs are designed to influence a person's attitude towards solar. To model the effects of informational interventions within the SECAD model we have justified two alternatives for how an agent's attitude *sia* will be modified when exposed to information resources.

- Maximal Effect Updating

We assume that each follow-on agent that encounters information disseminated from our modeled interventions will become attitudinally activated ($sia_i > sia_{thresh}$). The amount of solar adoption driven by these "perfect information programs" is a theoretical upper limit to whatever can be achieved for each intervention within the model. However, this "idealized attitude" adjustment allows us to easily evaluate competing informational intervention strategies against one another by evaluating the upper bound for each strategy.

- Relative Agreement Updating

Relative agreement updating builds upon the theory developed within the original SECAD model. Unlike the relative agreement process which takes place in the SECAD model 4 times per quarter, intervention updates only occur in time periods the intervention is active (For these experiments this is always at initialization t=0). At each time-step, seeds – which have high attitude - will update using relative agreement with all the follow-ons they are connected to. The effect of these updates will be to increase follow-on agent attitudes throughout the model.

How seeds are selected

Two targeting mechanisms are used for identifying seed agents within the interventions:

- Random selection

From the pool of potential seed agents, we randomly select seeds. This targeting strategy represents a minimum cost approach to selecting an information program participant.

- HighK selection

From the pool of potential seed agents, we select seeds that have the highest number of connections (K) to other agents. Essentially, we identify the agents with the most potential follow-ons. This targeting strategy represents a maximum cost approach to selecting an information program participant, who potentially can influence the most follow-on agents. Other advanced seed targeting techniques were considered, however implementation of these methods is beyond the scope of this report.

Intervention Timing

When modeling each intervention within SECAD we generate seed and follow-on agents only once – during initialization at t=0. While "in reality" information programs are likely to be carried out over a duration of time, for the purpose of these experiments we seed information only once so the effect of each intervention can be observed within SECAD over time. Seeding at multiply time steps would complicate separating the adoptions generated by each individual seeding event.

Intervention Design

The design of each individual intervention is summarized in the Table 2 below. Interventions are designed to approximate the reality of each of the four selected interventions. The success of each adoption is measured by its ability to generate additional adoptions over the baseline (no-intervention) model.

Program	**Seeds / Follow-On Rate**	**Mechanism within model**
Solar Champions:	**Seeds:** Agents that are seeded with information are Solar Champions. Solar Champions are trained by the utility/Solar advocacy organization and disseminate information to their immediate social network. **Follow On:** Follow-ons are the agents within the solar champion seeds social network.	**Initial Targeting:** To be a champion (seed) an agent must have sia greater than $sia_{threshold}$. At initialization agents with highest attitude ($sia>sia_{threshold}$) are identified as potential champions. From the pool of potential champions, we select agents as champions (seeds) randomly or based on high K. Follow-ons are agents that are with the champions immediate social network (Alters). **Operation:** The information effect of agents is passed on to follow on agents using relative agreement algorithm or 'maximal effect'.
Solar Ambassadors	**Seeds:** Agents that are seeded with information are Solar Ambassadors. Solar ambassadors are a select group (phone book) of agents who have adopted solar. **Follow On:** Follow-ons are agents who are interested in installing solar but require more information. They reach out to ambassadors to get more information.	**Initial Targeting:** At initialization agents with who have adopted solar are identified as potential ambassadors. From the pool of potential ambassadors, we select agents as ambassadors (seeds) randomly or based on high K. Potential follow-ons are agents within the model that are close to being attitudinally activated (This is calculated using a threshold of $0.6sia_{threshold}$.) These agents do not need to have any prior social or geographic connection with ambassadors. **Operation:** A network edge that connects each agent within our follow-on pool and our chosen ambassadors is created. This is actioned by adding the ambassadors to the targets alter network.
Porch Talk	**Seeds:** Agents are seeded with information to host porch talks. Porch talkers are agents who are adopters. Porch talks disseminate information to their immediate geographical network. **Follow On:** Follow-ons are the agents within the solar champions geographical network.	**Initial Targeting:** At initialization, from a pool of all the agents in the model who are adopters we -randomly or using High K – select a subset of adopters to host porch talks. These are the seeds. We then determine a subset of the seeds immediate geographical neighbors. This pool is refined using a participation rate. These are the follow-ons. **Operation:** The information effect of seed agents is passed on to follow-on agents using the relative agreement algorithm or 'maximal effect'.
Celebrity Advocates	**Seeds:** Agents that are seeded with information are celebrities. Celebrities able to transcend social and geographical networks within the model and disseminate information to any agent within the model. In this model only 20 agents are seeded.	**Initial Targeting:** The celebrity agents we seed with information do not exist within the SECAD model. We generate attitudinally activated celebrity seed agents within the model with *sia* between 0.6 and 1 (Unif[1,0.6,1]) and U = 1/*sia*. The pool of potential follow-ons for this intervention are all the agents within the SECAD model.

	Follow On: All agents are potential follow-ons**.**	**Operation:** The information effect of seed agents is passed on to follow-on agents using the relative agreement algorithm or 'maximal effect'.

Table 2: Describes the four interventions modelled in this research and explains their operation within the model

SECAD Setup

Each intervention is simulated within SECAD over a 6-year period. To generate adoption information each iteration of the SECAD model runs 5 batches of 24 quarter individual runs.

Seeds vs Follow-On Phase Diagrams

Most our results are presented as phase diagrams that track additional adoptions generated by each intervention as a function of seed quantity and follow on rate. Phase diagrams allow visualization of the effectiveness of each intervention as a function of the number of seeds and the seeds ability to generate follow-ons. This is a useful visual tool for attempting to view changes in adoption between caused by the intervention experiments.

Phase diagrams are generated by 1920 separate parameter-blast iterations of each intervention to explore the entire parameter space. Parameter-blasts iterations are conducted by randomly generating the seed quantity (1-500) and follow on rate (0-1) prior to each run. The solar PV adoptions plotted within the phase diagram results are the additional adoptions generated by the intervention compared to the empirically observed adoptions in 2014.

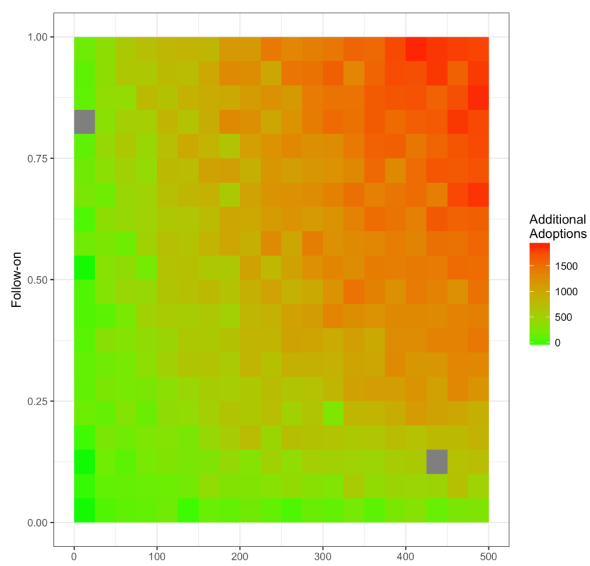

Figure 3 Example phase diagram.

Measuring the Value of Information and Economic Interventions

We use the SECAD virtual laboratory to test the efficacy of various solar information interventions. As informational resources are dispersed within the model they will alter an agent's *sia* and drive solar adoption within the model.

To assess the efficiency of informational experiments within SECAD it is necessary to establish a framework for measuring the value of informational interventions we model. This allows experimental interventions within the SECAD model to be compared to the effectiveness of real-word informational and economic interventions. To facilitate these comparisons, we use the following method to measure the cost of informational interventions in SECAD.

The method we utilize is a comparison of the return on investment – measured in additional adoptions - between our experimental informational intervention and a randomly dispersed economic intervention within the model. Return on investment or additional adoptions in SECAD is measured by total increased solar adoptions over the observed empirical adoptions in Austin during 2008 -2013.

$$AA = A_i - A_e \tag{1}$$

where:

AA is additional adoptions

A_i is the amount of adoptions for an informational intervention

A_e is the amount of observed empirical adoptions.

The economic intervention we model in SECAD simply measures the additional adoptions created by randomly selecting agents within the model and seeding them with solar PV. Within SECAD this simply involves changing the seed agent's adoption status from non-adopter to an adopter at initialization. To model the same parameter space as our information interventions we randomly seed between 1 and 500 agents and record the resulting additional adoptions. To measure the effectiveness of the economic intervention we evaluate the regression:

$$AA_e = \beta_e \times S_e + c_e \tag{2}$$

where:

AA_e is additional adoptions from the economic intervention

β_e is the amount of additional adoptions for one more economic seed

S_e is the amount of economic seeds

c_e is the mean additional adoptions with 0 economic seeds.

This result of this regression can then be compared to the following regression on each of the phase diagrams generated by our information intervention experiments:

$$AA_i = (\beta_{i,s} \times S_i) + (\beta_{i,f} \times FOR) + c_i \tag{3}$$

where:

AA_i is additional adoptions from the informational intervention

$\beta_{i,s}$ is the amount of additional adoptions for one more informational seed

$\beta_{i,f}$ is the amount of additional adoptions for increasing follow-on rate

S_i is the amount of informational seeds

FOR is the follow-on rate

c_e is the mean additional adoptions with 0 informational seeds.

The results of each of these regressions can be compared to provide an estimate of the differential return on investment provided by an economic seed compared to an informational seed. We achieve this by comparing the regression coefficients β_e and $\beta_{i,s}$, assuming both regressions are statistically significant. If we assume the cost of an economic seed is simply the cost of a solar system for that seed, we the ratio of $\beta_{i,s}/\beta_e$ provides an estimate of the how many solar systems each informational seed is worth. This result gives a simple indication of how much each information seed is worth, and how much a real-world solar information intervention program should be willing to pay each seed.

Results

In this section, we present the results of the parameter blast simulations described in the methods section above. For each intervention, results are presented on phase diagrams that evaluate additional adoptions generated over the seed and follow on parameter space. For each intervention, we present the results for both random and HighK seeding. Within the phase-diagrams we are looking for discernable trends and growth in solar PV adoption resulting from the modeled information interventions.

Solar Champions

The phase diagrams for both HighK and random (Figure 4) seeding of the solar champions intervention are shown below. In both solar champion models, we observe that the information intervention has not resulted in significant enough additional adoptions to overcome the random stochasticity of adoptions in the SECAD model. We see no discernable adoption trend across the seed and follow on parameter space, and increases in either parameter fail to generate adoption patterns.

This result is further illustrated in Figure 5 which presents the observed empirical adoptions (yellow curve) in Austin over the 2008-2014 timespan against the adoption results generated by the solar champion intervention (red dots, black curve is mean adoptions). We see that the adoptions generated by the intervention are spread relatively evenly around the empirical adoptions curve, sometimes improving upon and sometimes underperforming the empirical adoptions. We see that additional adoptions tracks empirical adoptions relatively closely and our intervention has not caused a significant change in solar adoption.

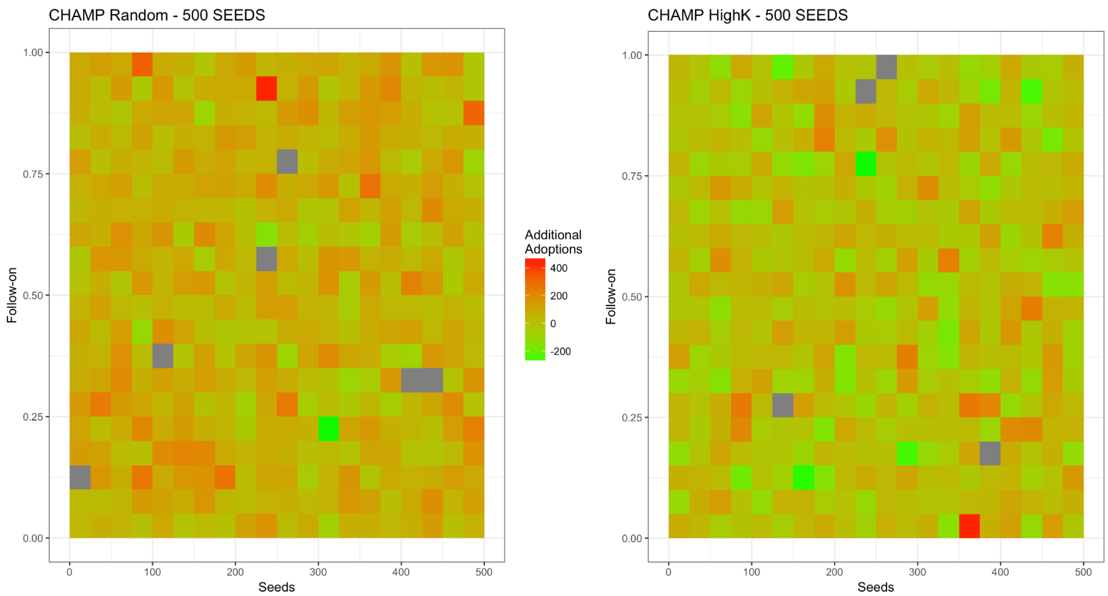

Figure 4 Phase diagram of solar champion intervention: Random (on left) and HighK (on right)

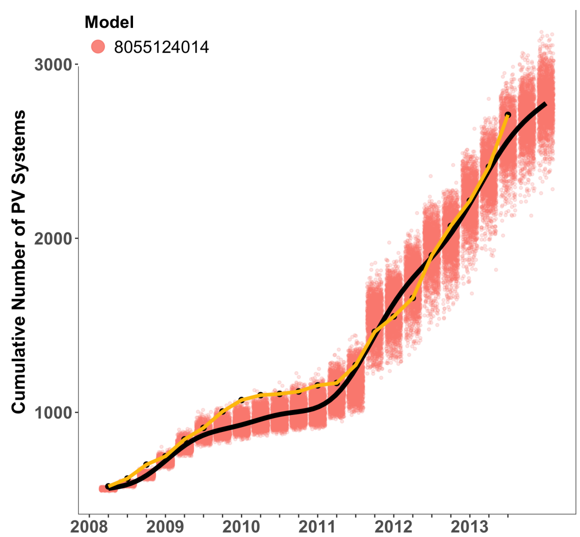

Figure 5 Observed adoptions of the solar champions intervention over time (individual observations in red and mean in black) against empirically observed adoptions between 2008 and 2014.

Porch Talks

The phase diagrams for both HighK and random (Figure 6) seeding of the porch talk intervention are shown below. Both phase diagrams give very different results, with random seeding significantly outperforming HighK seeding. This finding provides an interesting insight into the network locations of the HighK agents within the SECAD model, and the power of this targeting strategy. It appears that the failure of HighK targeting in this model is a function of the location of agents with HighK characteristics. It is apparent that all HighK agents exist within a small number of neighborhoods. This is sensible when considering how social networks are defined (see ABM overview), using geographical neighborhoods and an additional homophily constraint. Therefore, small and densely populated areas are likely to contain the majority of HighK agents.

As we add new seeds we continue to re-engage the same follow-on networks that have previously been targeted and solar information is continuously re-distributed within the same few networks. This strategy fails to drive any noticeable adoption trends within the model, and does not overcome the random stochasticity of adoptions in the SECAD model.

Alternatively, randomly selecting agents as seeds produces a noticeable adoption trend within the phase diagram, and has resulted in significant additional adoptions. As the number of seeds and adoption rate increase an obvious trend of additional adoptions emerges.

This result is observed despite random seeds having less follow-ons (by definition) then HighK seeds. It appears the relative success of random seeding is caused by the larger cumulative follow-on network the intervention can reach compared to HighK seeding. While each random seed may have less individual follow-ons, it is likely that each of these follow-on groups is unique. While on the other hand HighK seeds have follow-on groups, it is likely these groups are highly similar and the complete intervention fails to spread solar information and cause solar adoption.

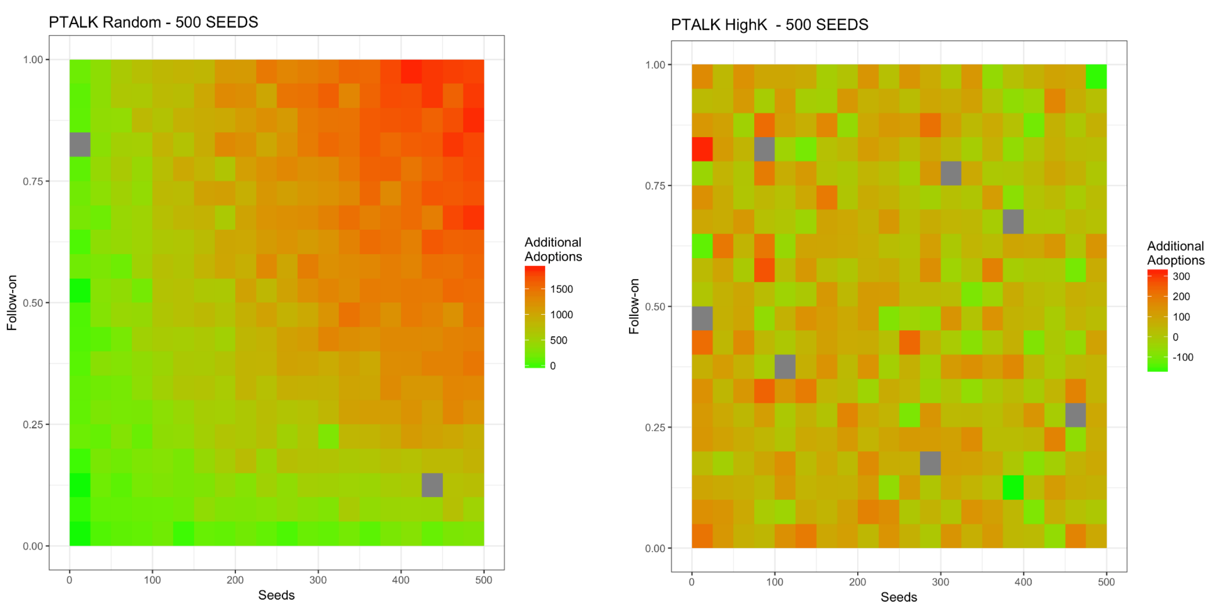

Figure 6 Phase diagram of porch talk intervention: Random (on left) and HighK (on right)

Solar Ambassador

The phase diagrams for both HighK and random (Figure 7) seeding of the solar ambassador intervention are shown below. In both phase diagrams, we observe that the solar ambassador intervention has resulted in significant additional adoptions above the empirically observed adoptions in 2014. The adoption trends within the phase diagrams clearly indicate that the solar ambassador program has successfully driven adoption within the model. Even with relatively few seeds and low follow-on rates an observable additional adoption trend emerges.

The random and HighK models for solar ambassador both generate very similar phase diagrams. This is expected as the solar ambassador intervention does not rely on the seeds existing networks to spread information, rather information is spread to follow-on agents by connecting them to a seed agent that they were not previously connected to. Therefore, it is unlikely that targeting seed agents based on their existing networks (as is done in HighK) will generate significantly different results than randomly seeding agents.

Additional adoptions in the phase diagram increase significantly across the vertical axis of the phase diagram. As the number of follow-ons connected to each seed increases, so does adoption within the model. However, the phase diagrams appear to show a weaker correlation between the number of seeds and additional adoption within the model. This result is confirmed by multivariate linear regression of follow on rate and number of seeds on additional adoption. The regression confirms that the seeds parameter is not related to the response. This result is problematic as it indicates that the number of seeds is unrelated to the response. It is likely that this is an artefact of a poorly specified seed variable within the model, since each seed updates with the same group of follow-ons within this model the marginal effect of additional seeds is rapidly reduced after only a few seeds are included in the model.

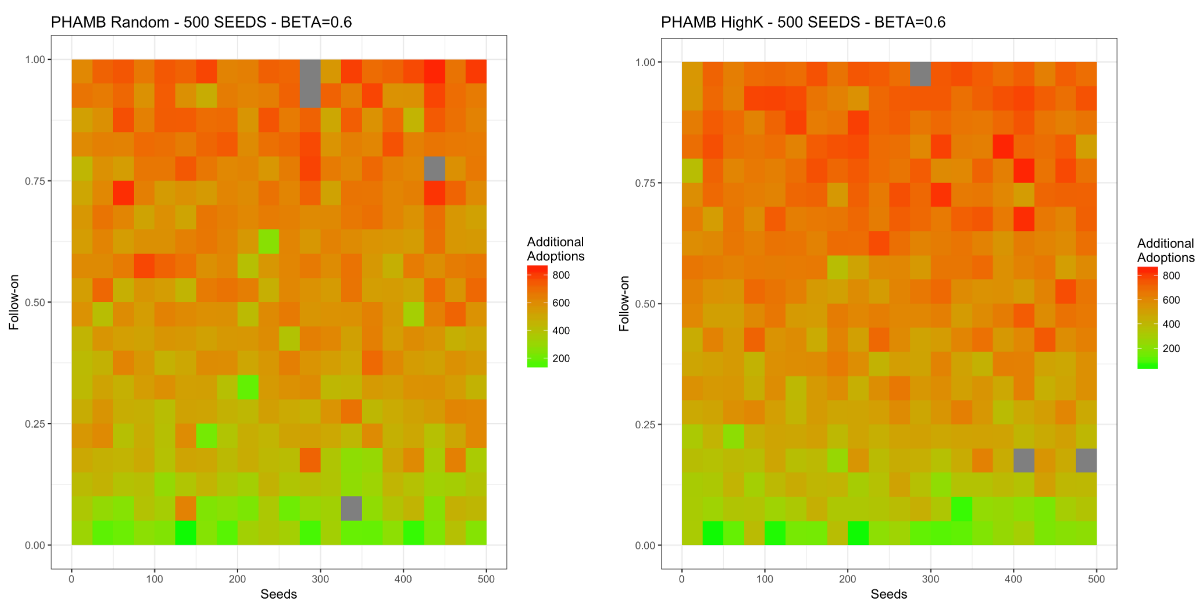

Figure 7. Phase diagram of phone ambassador intervention: Random (on left) and HighK (on right)

Celebrity Advocates

The phase diagrams for both HighK and random (Figure 8) seeding of the celebrity advocate intervention are shown below. The celebrity intervention only explores the seed parameter between 1 and 20. In both phase diagrams, we observe that the intervention has resulted in significant additional adoptions above the empirically observed adoptions in 2014. The clear adoption trends within the phase diagrams clearly indicate that the celebrity advocates have very successfully driven adoption within the model. As the number of seeds and adoption rate increase an obvious trend of additional adoptions emerges. The effectiveness of the celebrity intervention is somewhat expected, as celebrities have access to the largest follow-on group within the model and do not require a connection to the follow-ons.

This result is further illustrated in Figure 9, which again compares the observed empirical adoptions (yellow curve) in Austin over the 2008-2014 timespan against the adoption results generated by the celebrity intervention (red dots, black curve is mean adoptions). We see that at a very early time the adoptions generated by the intervention separates from the empirical adoptions curve.

An interesting observation within the celebrity phase diagrams is the extent to which random seeding outperformed targeted HighK seeding. HighK can generally be thought of as a more ‘administratively expensive’ seeding technique as it requires identifying network characteristics of each agent.

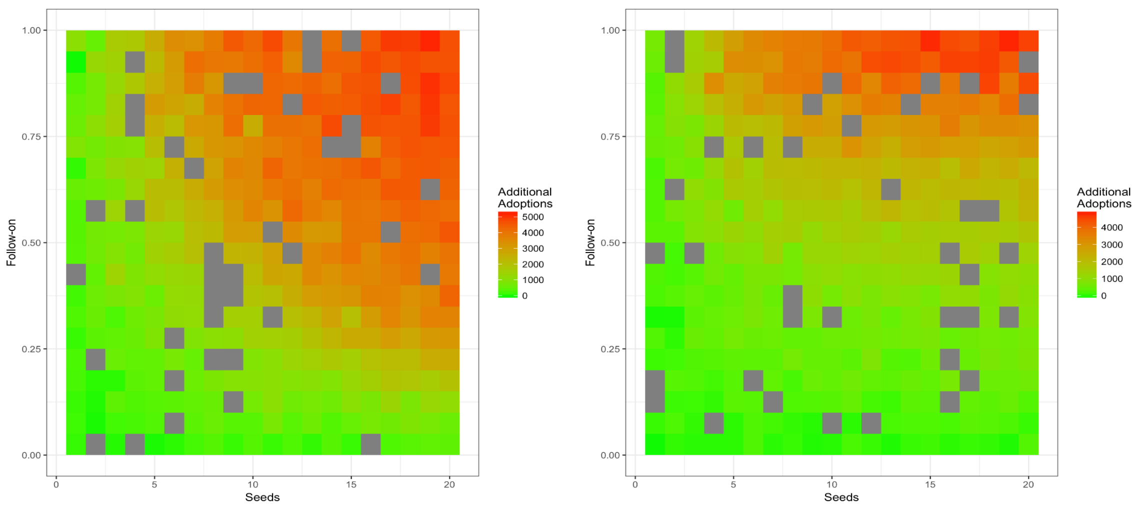

Figure 8. Phase diagram of celebrity advocate intervention: Random (on left) and HighK (on right)

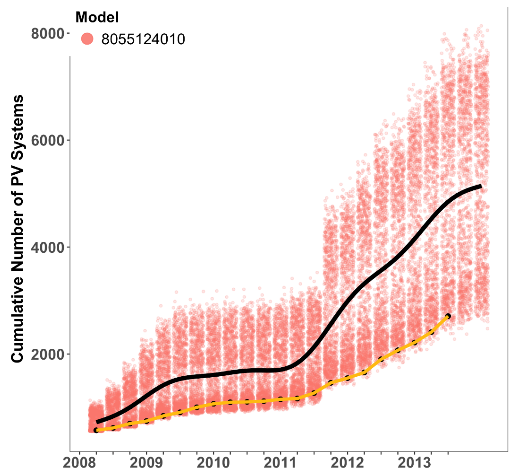

Figure 9. Observed adoptions of the celebrity advocates intervention over time (individual observations in red and mean in black) against empirically observed adoptions between 2008 and 2014

Determining the Value of Interventions

To evaluate the economics of the interventions modeled in this work we use the method described previously. We first evaluate the results of a simple economic intervention whereby we give each seed agent solar PV at initialization (t=0). This intervention has an easily evaluated economic cost of and value of:

$$Cost\ (\$) = N \times P \tag{4}$$

$$\text{Value}\ (\$) = N \times P \times \beta_e \tag{5}$$

where:

N is the number of seeds

P is the price of each solar system.

β_e is the amount of additional adoptions for one more economic seed

We then compare the performance of each information intervention against the performance of an economic intervention to determine the value of each informational seed compared to the cost of an economic seed.

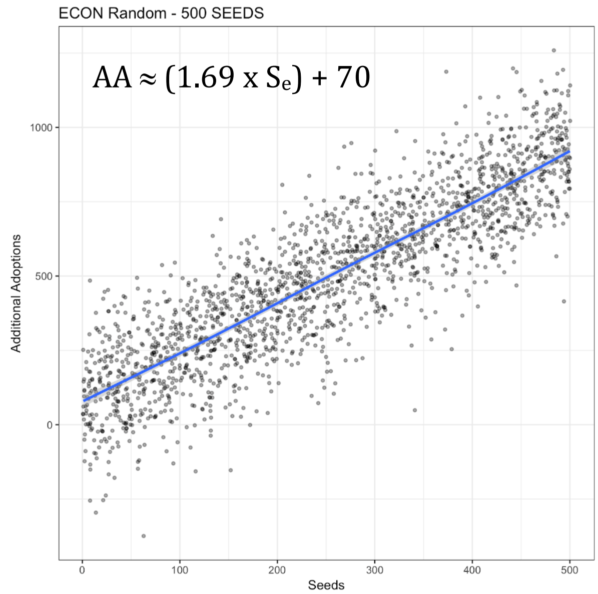

Figure 10. Regression on economic intervention

The results of the economic intervention are presented in Figure 10 above. We see from simple linear regression using equation (2) on these results that each additional economic seed (S_e) is worth approximately 1.69 (β_e) additional adoptions. We then perform multi-variate linear regression linear using equation (3) to determine $\beta_{i,s}$ for each of the informational interventions. These results are summarized in Table 3 below.

Program	**Targeting**	$\beta_{i,s}$	**Relative Value ($\beta_{i,s}/\beta_e$)**
Solar Champions	Random	0.02	0.012
	HighK	-0.02	-0.012
Porch Talk	Random	2.54**	1.5**
	HighK	-0.10**	-0.06**
Solar Ambassador	Random	0.03	0.018
	HighK	0.07**	0.04**
Celebrity	Random	168.1**	99**
	HighK	78.7**	47**

**** statistically significant**

Table 3 Assessing the value of information interventions.

The results of each of these regressions are compared in the right-hand column of Table 3 and provide an estimate of the differential return on investment provided by an economic seed compared to an informational seed. If we assume the cost of an economic seed is simply the cost of a solar system for that seed, the ratio of $\beta_{i,s}/\beta_e$ provides an estimate of the how many solar systems (or economic seeds S_e) each informational seed is worth.

Discussion

Designing Interventions to Succeed

A key goal of this research was to identify factors that cause solar information intervention to succeed. While we have not attempted to optimize interventions themselves, our results provide useful insights into the characteristics that define the success of our modeled interventions.

Interventions that rely on existing network connections (social network in SECAD) to spread information are less effective at driving solar adoption than interventions that force agents to create new connections. This is made clear by a comparison of the Solar Champions program to the other interventions we model. The Solar Champions intervention relies on agents spreading information about solar to the agents within their existing social networks. Unlike the other interventions we model, seeds and follow on agents in this model are already connected, thus the effectiveness of this program essentially relies on seed agents knowing as many unique follow-on agents as possible. However, as our results demonstrate even with up to 500 seed agents this intervention is not powerful enough to generate observable additional adoptions. These results indicate that spreading information using the existing social network of agents is a poor strategy for generating solar adoptions.

In contrast to this result, all interventions (with the exception of Porch Talks - HighK which is discussed later) that forged new network connections between seed and follow-on agents demonstrated clearly observable increases in adoption. These interventions create connections between seed agents and follow-ons outside of each agents existing social network. Information about solar is able to escape beyond the seed social network clusters that are targeted in solar champions and reach follow-on agents that are connected within other new social networks. This is a finding that remains sensible when translated to the "real-world", interventions that force people to interconnect and exchange information are likely to be more successful.

Another key observation within our modeling is the extent to which random targeting of seed agents outperforms HighK targeting. This would appear to be contradictory finding, as HighK is thought of as a more expensive form of targeting as it requires assessing the "popularity" (K) of each agent. However, the result in fact highlights the limitations of HighK targeting.

The limitations of HighK targeting is best evidenced in the results from the Porch Talk program. Looking at Figure 6 we see that within the Porch Talk program HighK targeting significantly underperforms compared to random targeting. The problem when targeting seeds using HighK is that agents with HighK have a high probability of being connected to one another. In the case of the Porch Talk program it is clear that a majority of the agents with seeded due to HighK resided within the same network. Therefore, we repeatedly provided information to the same group of follow-on agents but were unable to reach any agents outside the HighK neighborhood. In contrast random seeding - while inexact – managed by chance to spread information to a significantly larger follow-on network than HighK's saturation of an individual network.

These observations inform the central finding of this work, that information programs that are able to reach the largest unique network of follow-on agents will be the most successful in promoting diffusing of solar PV. Intervention design that forces solar advocates (seeds) to interact with people (follow-ons) outside their existing social networks and who may not share similar characteristics as them (K) will lead to better outcomes.

Evaluating the Economics of Interventions

From Table 3 we see that as expected celebrity interventions have the highest value of all seeds and are worth over 50 times the cost of an economic seed. Therefore, as a coarse approximation if the cost to hire a celebrity advocate was less than 50 solar units it would be an economical decision. The same analysis can be applied to each of the other programs to provide an estimate of a threshold value for each intervention seed.

Finally, while it may seem obvious that celebrities provide the best value of all the information programs, it is also true that a celebrity would be the most expensive person to employ as a solar advocate. While the value of a porch talks and solar ambassador seed may appear comparatively small, they are also likely to be orders of magnitude less expensive than a celebrity. Therefore, it is important to note that if interventions generate statistically significant additional adoptions they are worth evaluating against the cost of seeds.

Conclusion and Policy Implications

In this research we identify that information interventions that spread beyond existing social networks are more effective than those that rely solely on social networks. Put another way, we find that the creation of new "weak ties" facilitates the effective diffusion of information (Granovetter, 1978). We also find that seeding highly connected agents is inferior to random seeding. These findings have several interesting policy implications.

Based on these results we recommend designing solar information interventions to maximize the amount of interactions between people in different social groups. This allows information to travel beyond a finite number of existing social groups and instead connects a larger number of social groups. Information spreads within these larger interconnected social groups over time via word of mouth and peer effects. Interventions should therefore be designed such that each "seed" or influencer is able to interact with people beyond their own social network.

We also find that repeatedly seeding highly connected agents is an ineffective strategy. Programs that repeatedly identify seeds based on simple characteristics such as popularity, location or wealth may find similar limitations. Seeding by these characteristics will increase the likelihood that each new seed is belongs to a similar social group as a previous seed. Therefore even with large numbers of seeds, the program reaches a substantially smaller number of social networks. For successful interventions seeds should be selected that are able to reach the broadest number of new social groups.

The SECAD model used in this research is validated for Austin, Texas. Necessary modifications should be made when applying the findings presented in this paper to cities with different economic and policy contexts.

Future Work

This research presents several opportunities for further refinement and study. Improved modelling of the cost of each information intervention will facilitate better comparisons of the return on investment of each program. One potential method would be to use the number of follow-ons a seed agent has at initialization (t=0) as a proxy for their cost. For example it would be expected that a celebrity seed with 100,000 follow-ons is 10,000 times more expensive than a program volunteer seed with 10 follow-ons.

Furthermore, increasingly granular modeling of the quality of information has the potential to improve the finding of this work. For example, Rai, Reeves & Margolis (2015) find that the influence of neighbors and installers to be strong motivators toward PV adoption. An ability to model the "quality of information" or trustworthiness of each individual seed would improve the reliability of this work.

In this research we test only two seed targeting strategies, random and HighK. However, several more powerful network centrality theories exist. For example, Kitsak et al. (2010), offer a novel theory for determining the most "influential" nodes in a network. Further work could test these theories within the SECAD model to see whether they are able to outperform random and HighK seeding.

Finally, all interventions modeled in this research were purely informational. No consideration was given to modeling economic interventions – for example a change in the PV rebate – in combination with informational interventions. Further work should explore combinations of economic and information interventions to understand if they offer better return on investment.

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